

# Variational Methods for Latent Variable Problems

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Ryan Giordano (for Johns Hopkins Biostats BLAST working group)

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Massachusetts Institute of Technology

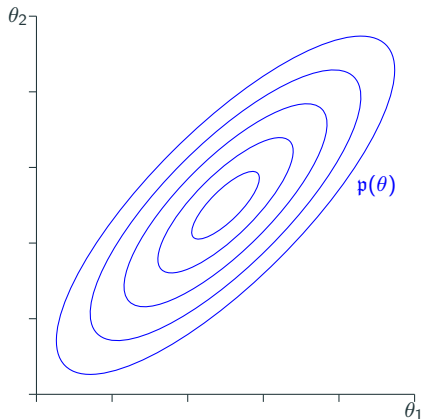
Outline for today:

- Some examples of latent variable models
- A template: The Neyman-Scott “paradox” and marginalization
- Bayesian versus frequentist approaches to marginalization
- The classical EM algorithm (in brief)

Next week, we will build on these ideas to present more general variational inference.

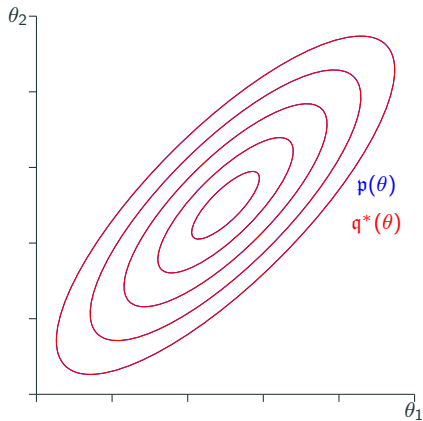
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$$q^*(\theta) = \operatorname{argmin}_{q \in \mathcal{Q}} \text{KL}(q(\theta) || p(\theta))$$



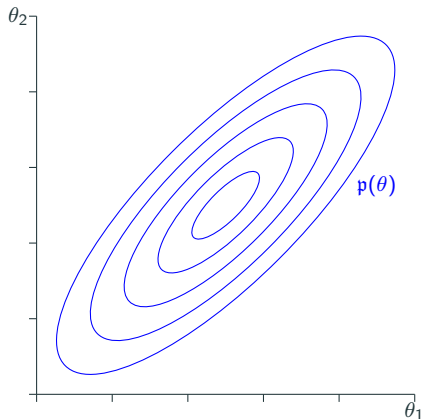
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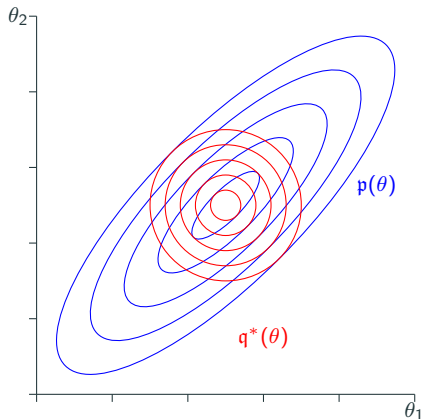
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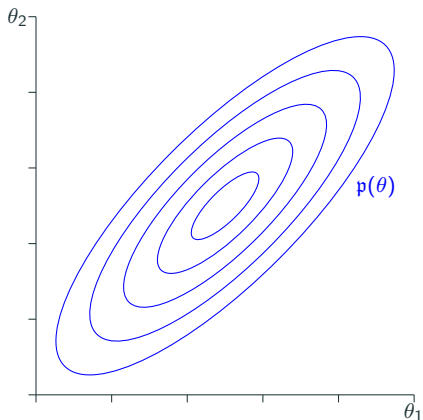
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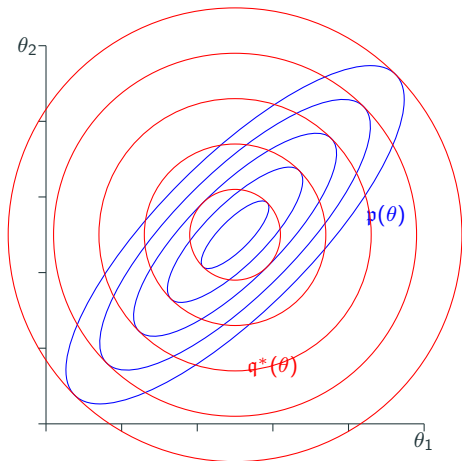
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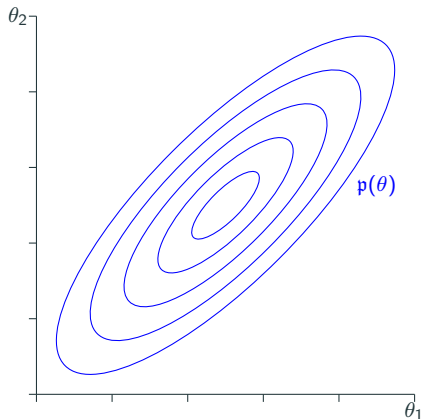


Recall that

$$\text{KL}(q(\theta) \parallel p(\theta)) = -\mathbb{E}_{q(\theta)} [\log p(\theta)] + \mathbb{E}_{q(\theta)} [\log q(\theta)]$$

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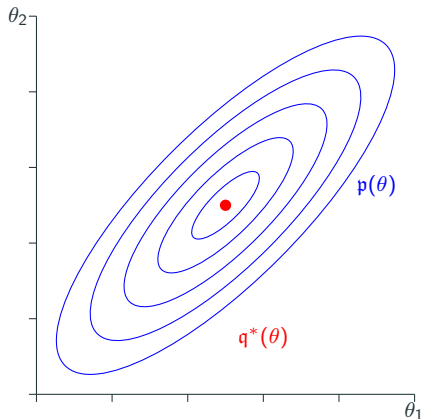


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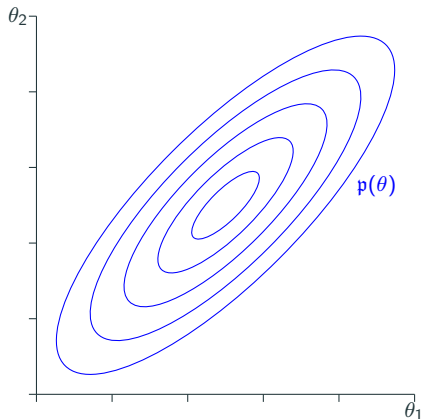


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